Long-Term Electricity Load Forecasting Based On Cascade Forward Backpropagation Neural Network

Widi Aribowo and Supari Muslim
State University of Surabaya.
widiaribowo@unesa.ac.id

***Abstract*— Nowadays, the Electrical System has an important role in all sectors of life. Electricity has a strategic role. Accuracy and reliability in electricity load forecasting is a great key that can help electricity companies in supplying electricity efficiency, hence, reducing wasted energy. In addition, electricity load forecasting can also help electricity companies to determine the purchase price and power generation. Long-term forecasting is a method of forecasting with a span of more than one year. The historical data will be a reference in solving the problems. This research propose the concept of cascade forward backpropagation for long-term load forecasting. The advantage of this concept is that it can accommodate non-linear conditions without ignoring the linear conditions. This study compared the results of the original data, Feed Forward Backpropagation Neural Network (FFBNN) and Cascade Forward Backpropagation Neural Network (CFBNN). The results were measured by comparing Mean Absolute Deviation (MAD) and Mean Absolute Percentage Error (MAPE).**

***Index Terms*— CFBNN; Long-Term Load Forecasting; MAPE; Neural Network.**

I. INTRODUCTION

Consistent with the development and technology advances, demand for the availability of continuous electricity is increasing. Every electricity company must know exactly the amount of maximum electrical energy that must be provided within a certain period of time. Sufficient electricity supply must be a priority for effective and efficient development, and electricity consumption is an indicator of the development of a sector or region. The climate change, technological development, and applicable energy policies can result in a sudden increase in peak demand. This can result in changes in demand forecasts for end-users. The increasing use of electrical energy must be anticipated by providing a more adequate electrical system in both quantity and quality.

One of the factors of a power system plan is the forecasting of electric power loads over a period of time. Forecasting is an activity to predict conditions within a certain period of time. Forecasting methods can be classified based on research objectives and methodology. Load forecasting has become a favorite field of research for more than 50 years. The essential step in energy guidance, mainly in electricity designing, is load forecasting, which involves a discussion based on the operation and planning of the power system. The weak accuracy of the estimated load will negatively impact the operating costs of the electricity company [1]. Load forecasts are the key for an energy provider, economic consortium, and other corporations in electric energy. Forecasts for various time horizons are notable for various operations in the electric corporation and there are different methods of forecasting.

Load forecasting can be divided into four types based on period of time namely, the very short-term forecasts have a forecast range from a few minutes to an hour ahead used for real-time control [2], the short-term forecasts have a forecast period of one hour to one week, the medium forecasts have a span of time from one week to a year, and the long-term forecasts that are longer than one year. Long-term forecasting will become a guide for strategic planning and the construction of new power plants and transmission capacity because new projects take years to complete [3].

Long-term forecasting can be used to determine the annual peak load or energy demand within a period of 20 years. It can be used to schedule planning for expansion of production and distribution systems. Although long-term forecasting is not new in the study, analyzes that include sector breakdown and end use are very few [4]. Long-term forecasting has a very important role in planning the construction of new generating facilities and on the transmission line expansion [5-6]. Long-term load forecasting can provide guidance on energy policy and decisions from the government; hence, making it easier for companies in the electricity sector [7].

Several studies have been conducted to discuss the forecasting of electrical loads for short-term, medium-term and long-term. Generally, electricity load forecasting can be categorized into two methods, namely: the forecasting with statistical methods and the forecasting with artificial intelligence methods [8]. Although they are different model and forecasts, both the traditional methods and the artificial intelligence methods have similar feature, that is they depend on historical data, climate, population and several other factors.

Many researchers apply statistical methods, such as Generalized Autoregressive Conditional Heteroskedastic (GARCH) [9-12], Auto Regressive Integrated Moving Average (ARIMA) [13-16], and Support Vector Machine (SVM) [17-20], while methods based on Artificial Intelligence (AI) are widely used. AI in general has an adaptive advantage and is able to process fluctuating data. AI can provide high accuracy, because it has the ability to process non-linear functions. Many researchers have presented several uses of AI methods such as neural network [21-24], Particle Swarm Optimization [25-28], and Bee Colony [29-32].

This research will present long-term electricity load forecasting using the Cascade Forward Backpropagation Neural Network (CFBNN). The CFBNN method is used to estimate the different electricity load forecasting models. The concept of cascade is dynamic network architecture. The learning algorithm is closed to optimal for complex networks. The learning algorithm of cascade starts with only one neuron and can add new neurons during training. It can create a multilayer architecture. The neurons increase in the hidden layer step-by-step gradually, while training errors will be reduced [33]. The proposed method is tested using actual recorded data. The result of Load Forecasting are measured using Mean Absolute Deviation (MAD) and Mean Absolute Percentage Error (MAPE) to determine the algorithm performance of method. Forecasting results are compared with actual data and FFBNN methods to get the level of forecasting accuracy.

II. CASCADE FORWARD BACKPROPAGATION NEURAL NETWORK

The method of a cascade network is composed of input units, hidden units, and output units. The cascade network is the same as the feed-forward backpropagation neural network. The characteristic of the cascade network is that the input unit is connected to two branches, namely one branch is connected to a hidden unit and the other is connected directly to the unit of output. Each network from the input unit is given an adjustable weight. Connection paths from the input unit to the hidden unit are trained. In the next step, hidden units are added to the net and stored. Connection flow from the hidden unit to the output unit can be adjusted.

In the beginning, the Cascade network has a minimal topology, which the unit has the required inputs and outputs only. The cascade network is trained repeatedly until the smallest error is found. The error for each output will be calculated. Each hidden unit is always added to the network in a two-step process.

The first step, the candidate unit is connected to each network input unit, but it is not connected to the output of the unit. The weight of the connections from the input unit to the candidate units are adjusted to maximize correlation between the candidate output and the error in the output unit. Error is identified as the difference between the targets and the calculated output, multiplied by the derivative of output unit activation function. The amount will be reproduced from the output unit with the backpropation algorithm. When training is completed, the weights are saved and the candidate units become the hidden units in the network.

The second step begins when the new units are added to network. The second hidden unit is added using the same process. The process involves adding the new units and training weights from the previous step, and then weights are stored, followed by training all connections to the output unit. This process is carried out until the smallest error or the desired error is reached. The CFBNN is evaluated using Mean Square Error (MSE). The structure of CFBNN can be seen in Figure 1.

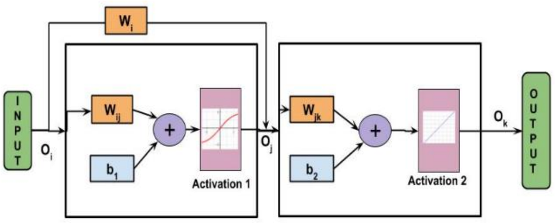

Figure 1: Cascade forward backpropagation neural network structure

CFBNN has inputs (O_1, O_2…….. O_i), i.e. long-term electricity load data. The Inputs Data is used in the training process.

$$O_j(t) = (\int \sum_{i=1}^{j} W_{ij} O_i(t) + b_1). \sum_{i=1}^{j} W_i . O_i(t)) \tag{1}$$

The W_{ij} is the weight from the input unit (O_i) and a bias (b_1) is added. Both weight (W_{ij}) and bias (b_1) are totaled up to activated them using the sigmoid function. The activations have to get an input value to the output using the sigmoid tangent hyperbolic function. The maximum value of the output of this function is 1 and a minimum of -1. The algorithm of this function is:

$$\int (O_j(t)) = \frac{1}{1 + exp^{(-O_j(t))}} \tag{2}$$

The activation in the second part uses the linear activation function. This step is done after summing the bias (b_2) and inputs from $O_j(t)$. The W_{jk} is the weight from $O_j(t)$. The algorithm $O_k(t)$ can be written as follows:

$$O_k(t) = \int (b_2 + \sum_{j=1}^{k} W_{jk}. \int O_j(t)) \tag{3}$$

The activation is done by using a linear function. The linear function will bring the input to a comparable output.

$$O_k(t) = f'(O_k(t)) \tag{4}$$

The output unit $O_k(t)$ matches the target according to the input during the training. The error is obtained by multiplying the derivative of the activation function:

$$\delta_i = (\delta_i - O_k) f'(O_i) \tag{5}$$

The weight improvements are used to correct new W_{jk},

$$\Delta W_{jk} = \alpha. \delta_i . O_j \tag{6}$$

The Learning Rate (α) has value normally from 0.1 to 0.5. The Learning rate is very influential in the training part. The weight (W_{jk}) is connected to the output unit with a hidden unit multiplied with δ_i.

$$\delta\_in_i = \sum_{j=1}^{k} \delta_i . W_{jk} \tag{7}$$

The error is obtained by multiplying δ_in_i by the derivative of the activation:

$$\delta_k = \delta_{in_i} . f'(O_j) \tag{8}$$

The weight improvements are used to modify ΔW_{ij}:

$$\Delta W_{ij} = \alpha. \delta_k . O_i \tag{9}$$

The output unit improves the weight (W_{ij}):

$$W_{ij}(new) = W_{ij}(old) + \Delta W_{ij} \tag{10}$$

The hidden unit modifies the weight (W_{jk}):

$$W_{jk}(new) = W_{jk}(old) + \Delta W_{jk} \tag{11}$$

Mean Squared Error (MSE) is the average of mistakes squared. MSE is calculated by comparing the output value ($O_k(t)$) and the target values ($T_k(t)$). The result, which is the difference between the squares divided by the number of variables (n) provides the error estimate.

$$MSE = \frac{1}{n}\sum_{k=1}^{n}(T_k(t) - O_k(t))^2 \quad (12)$$

III. Research Method

The research method is divided into three important parts. Each section has several concepts from input data process until the long-term electricity load forecasting output. The steps in this research can be seen in Figure 2.

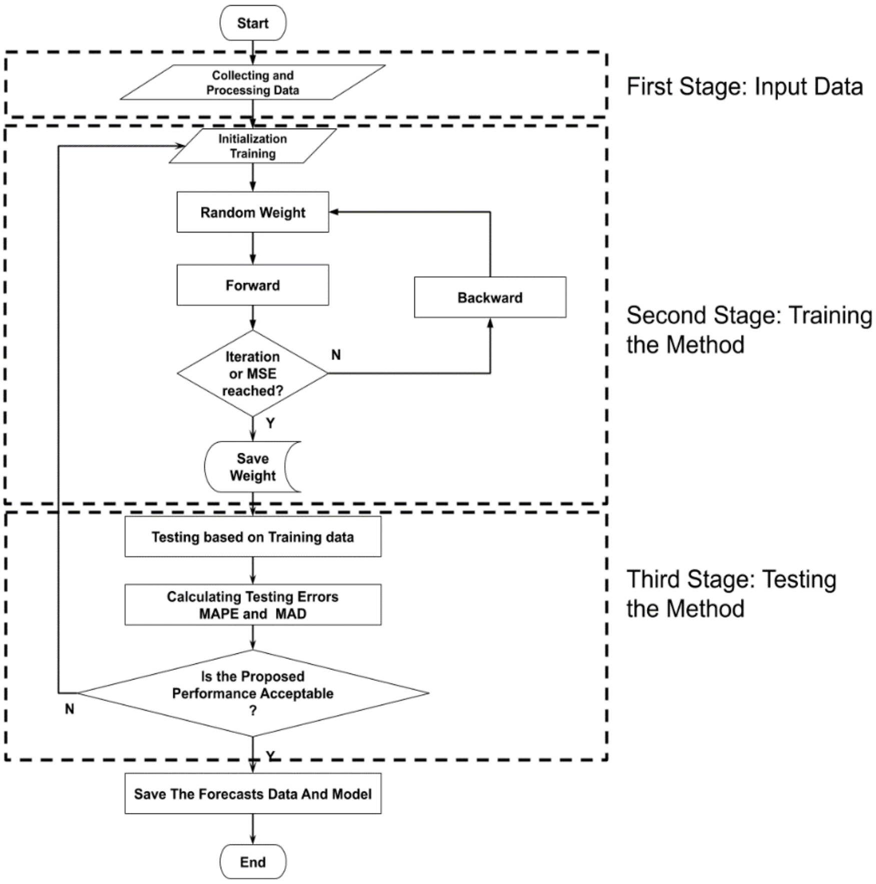

Figure 2: Flowchart of the research

In the first stage, training data were collected and processed to form groups. The data were used to estimate the peak of electricity load data in Indonesia from 2009 to 2019 and several factors that support the forecasting of electrical loads from 2000 to 2009. This data is a reference to determine the ability of the proposed method performance. The data can be seen in Figure 3.

In the second stage: Training the Method, the model is trained using the part of the input data. Training input parameters were developed. This training was carried out until it reached the desired epoch or MSE. The proposed CFBNN method can be seen in Figure 4.

At the training stage, data were collected and processed. The data used were data that affects the electricity load per year. The data was taken from 2000 to 2009. The data used were Gross domestic product data, electricity consumers both household or industry, coal production, crude oil production, export oil and gas, import oil and gas, and the peak of electricity load. The target as a reference was the peak load forecasting data for the 2009-2019 period. Data and targets were processed using CFBNN with several criteria that must be met. The parameters of the neural network can be seen in Table 1.

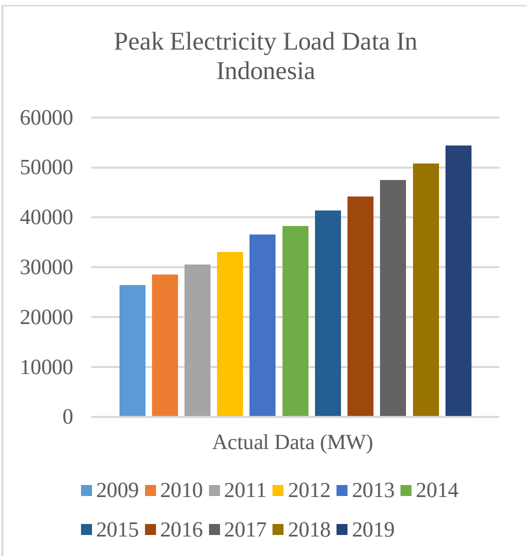

Figure 3: Chart of peak electricity load data Indonesia in the period 2009 – 2019

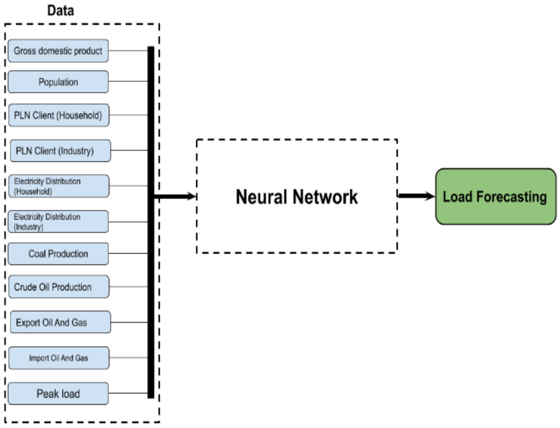

Figure 4: The proposed load forecasting model using cascade forward backpropagation neural network

Table 1
Parameter Proposed Cascade Forward Backpropagation Neural Network

Syntax	Parameter
Number Of Hidden Layer	5
Transfer Function For Hidden Layer	Hyperbolic Tangent Sigmoid Transfer Function (tansig)
Transfer Function For Output Layer	Linear Transfer Function (purelin)
Weight /Bias Function	Gradient Descent With Momentum (learngdm)
Epoch	1000
Learning Rate	0.1
Momentum	0.2

In the third stage: Testing the Method was done after calculating the optimal value of the proposed parameters (weights and biases), the model was tested using various error functions (MAPE and MAD). If the error obtained is unacceptable, the second stage was repeated.

IV. RESULTS AND DISCUSSION

The results were obtained after the neural network training process up to 1000 epochs. Table 2 shows the results of electricity load forecasting using the CFBNN and FFBNN methods with a hidden layer 5 and learning rate 0.1. The results in Table 2 show very small differences between the actual data, CFBNN and FFBNN results.

Table 2
The Result of Electricty Load Forecast (MWh)

Year	Actual Data	CFBNN	FFBNN
2009	26375	26375.00058	26375.00000
2010	28568	28567.99987	28567.99998
2011	30540	30539.99999	30540.00002
2012	32991	32991.00043	32991.00003
2013	36489	36489.00003	36488.99995
2014	38242	38242.00002	38242.00006
2015	41309	41309.00002	41309.00000
2016	44143	44143.00003	44143.00000
2017	47403	47403.00000	47403.00000
2018	50807	50806.99998	50806.99999
2019	54397	54396.99959	54397.00000

The final step in this research is to measure the performance of the CFBNN and the FFBNN method. Performance measurement was done by using Mean Absolute Deviation (MAD) and Mean Absolute Percentage Error (MAPE). MAPE is a method that calculates the difference between the original and the forecasting data. If the difference is absolute, it is then counted as the percentage of the original data. The percentage results were then obtained by the mean value. A model has a very good performance if the MAPE value is below 10%. Although the results of the study indicate that the MAPE value of the FFBNN is much smaller than the value of the CFBNN.

In this research, experiments using variations of neural network parameters were conducted to measure the performance of the proposed method. Making changes to the value of the learning rate can have various effects for the Mean Absolute Deviation (MAD), Mean Absolute Percentage Error (MAPE) and Mean Squared Error (MSE) resulting from the training process. The variable of parameters used is the learning rate and the hidden layer. In Table 3, the use of hidden layers 5 resulted in the Value of the MAPE and MAD for CFBNN to have a smaller value compared with the FFBNN method. The different value of MAPE from the CFBNN and the FFBNN is 2.26x10^{-06} and the different value of MAD from CFBNN and FFBNN is 5.76x10^{-06}, resulting in a contradictory result from the previous experiement. In the hidden layer 10 with learning rate 0.5 and hidden layer 15 with learning rate 0.25, the MAPE and MAD value for FFBNN have better performance.

Table 3
The Result of MAPE and MAD

Parameter		CFBNN		FFBNN	
Hidden Layer	Learning Rate	MAPE	MAD	MAPE	MAD
5	0.10	4.60x10^{-07}	1.54x10^{-05}	5.11x10^{-08}	1.82x10^{-06}
	0.25	9.59x10^{-07}	4.18x10^{-05}	7.27x10^{-06}	4.18x10^{-05}
	0.50	7.21x10^{-07}	2.97x10^{-05}	6.74x10^{-07}	2.6x10^{-05}
10	0.10	3.37x10^{-08}	1.35x10^{-06}	4.95x10^{-07}	1.82x10^{-05}
	0.25	4.04x10^{-07}	1.51x10^{-05}	3.39x10^{-07}	1.26x10^{-05}
	0.50	4.43x10^{-06}	0.000179	9.32x10^{-07}	3.59x10^{-05}
15	0.10	3.43x10^{-07}	1.36x10^{-05}	3.76x10^{-07}	1.41x10^{-05}
	0.25	5.76x10^{-05}	0.002029	5.22x10^{-08}	2.05x10^{-06}
	0.50	2.74x10^{-07}	9.99x10^{-06}	2.24x10^{-07}	9.19x10^{-06}

In Table 4, the proposed CFBNN method has better epoch and time-training than the overall FFBNN method. The lowest epoch value of CFBNN occurs in the number of hidden layers 15 with a learning rate 0.1. The epoch value of CFBNN is 279 and the training time is 6 seconds. On the other hand, the greatest epoch value exists when using 15 hidden layers and a learning rate of 0.5. The lowest epoch of FFBNN occurs in the number of hidden layer 10 with learning rate 0.25. The epoch value is 492. On the other hand, the biggest value of epoch is in the hidden layer 15 with learning rate 0.25.

Table 4
The Result of Epoch and Time

Parameter		CFBNN		FFBNN	
Hidden Layer	Learning Rate	Epoch	Time of Training	Epoch	Time of Training
5	0.1	339	0:00:06	444	0:00:07
	0.25	517	0:00:07	521	0:00:08
	0.5	280	0:00:05	557	0:00:08
10	0.1	487	0:00:09	540	0:00:09
	0.25	400	0:00:06	492	0:00:08
	0.5	423	0:00:08	582	0:00:11
15	0.1	279	0:00:06	547	0:00:10
	0.25	445	0:00:10	815	00:00:15
	0.5	545	0:00:13	547	0:00:10

The values MSE of CFBNN and FFBNN methods can be seen in Table 5. The CFBNN with hidden layer 5 has the smallest MSE with learning rate 0.1 and the FFBNN with hidden layer 5 has the smallest MSE with learning rate 0.1. The CFBNN method has a better MSE value when using hidden layer 10 with learning rate 0.25. The FFBNN has the smallest MSE using hidden layer 5 with learning rate 0.1. On the other hand, The CFBNN has the biggest value of MSE using hidden layer 15 with learning rate 0.25. The FFBNN has the biggest value of MSE using hidden layer 5 with learning rate 0.25. Overall, the setting of hidden layer and learning rate can affect the results of the CFBNN and FFBNN. Increasing the learning rate can decrease MSE both CFBNN and FFBNN.

Table 5
The Result of MSE

Parameter Global		CFBNN	FFBNN
Hidden Layer	Learning Rate	MSE	MSE
5	0.10	6.48×10^{-08}	7.74×10^{-10}
	0.25	3.51×10^{-07}	1.24×10^{-05}
	0.50	1.43×10^{-07}	1.59×10^{-07}
10	0.10	3.07×10^{-10}	5.84×10^{-08}
	0.25	4.27×10^{-08}	3.12×10^{-08}
	0.50	2.54×10^{-08}	1.72×10^{-05}
15	0.10	4.13×10^{-08}	3.15×10^{-08}
	0.25	0.000688	1.11×10^{-09}
	0.50	1.71×10^{-08}	3.15×10^{-08}

V. CONCLUSION

CFBNN methods for forecasting long-term electricity loads have been discussed in this paper. The data and the algorithm are very important in this study. The research shows that the CFBNN method were able to forecast long-term electricity loads. The values of MAPE and MAD were very small.

The average MAPE of the CFBNN method was better than the FFBNN method which is 7.24963×10^{-06}. While the average MAPE of the FFBNN method is only 1.04101×10^{-05}.

On the other hand, the average MAD value Of the FFBNN method was better than the CFBNN method, which is 1.79611×10^{-05}. The value of CFBNN method was 0.000259434.

In addition, based on simulations, the CFBNN method had better epoch and time-training compared to the FFBNN method. The CFBNN method was faster in conducting training.

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